System Identification of Vessel Steering With Unstructured Uncertainties by Persistent Excitation Maneuvers

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***Abstract*—System identification of vessel steering associated with unstructured uncertainties is considered in this paper. The initial model of vessel steering is derived by a modified second-order Nomoto model (i.e., nonlinear vessel steering with stochastic state-parameter conditions). However, that model introduces various difficulties in system identification, due to the presence of a large number of states and parameters and system nonlinearities. Therefore, partial feedback linearization is proposed to simplify the proposed model, where the system-model unstructured uncertainties can also be separated. Furthermore, partial feedback linearization reduces the number of states and parameters and the system nonlinearities, given the resulting reduced-order state model. Then, the system identification approach is carried out, for both models (i.e., full state model and reduced-order state model), resorting to an extended Kalman filter (EKF). As illustrated in the results, the reduced-order model was able to successfully identify the required states and parameters when compared to the full state model in vessel steering under persistent excitation maneuvers. Therefore, the proposed approach can be used in a wide range of system identification applications.**

***Index Terms*—Extended Kalman filter, feedback linearization, nonlinear vessel steering, persistent excitation maneuvers, ship model identification, system identification, vessel steering system.**

I. Introduction

A. Introduction

ALMOST all ancient civilizations were developed near major rivers and waterways [1]. These rivers and waterways were accommodated with several important life supporting resources in human history. As the civilizations were overaccumulating with their resources (i.e., agriculture, fishing, salt, etc.), trading routes among them were expanded, where navigation was placed as an important role in trading of goods and services. The interest since ancient time to present in ocean navigation increased and resulted in various ocean going vessels reaching congested sea routes in several regions of the planet [2]. Therefore, to accommodate current ocean navigation requirements, sophisticated ocean vessels associated with advanced control systems are mandatory. One should note that almost all the advanced control and guidance mechanisms [3], [4] in ocean going vessels/vehicles are associated with various mathematical models [5], [6]. Therefore, the field of system identification in ocean going vessels plays an important role in the design process of the respective controllers.

The development of mathematical models of ocean going vessels is complex, when compared to land and aerial vessels, due to the associated nonlinear hydrodynamic forces and moments. Therefore, various research studies on ship dynamics are being developed in several directions: 1) steering and maneuverability, the study of vessel motions in absence of wave excitations, generally denominated as maneuvering, thus corresponding to a situation where the vessel motions are under calm water conditions; and 2) seakeeping, that is, the study of the vessel motions under the presence of wave disturbances. In the recent literature, various mathematical models combining both directions (i.e., steering and maneuverability, and seakeeping) can also be found.

However, a unified seakeeping and maneuvering model in vessel dynamics is also presented in the recent literature [7]. This proposed model consists of a large number of system states and parameters, therefore the proposed approach can encounter difficulties in system identification, where the controller design process can be degraded. One should note that system identification (i.e., parameter and state estimation) plays an important role in the controller design process. State and parameter estimation of a higher order system often can be affected by the divergence (i.e., the estimated state and parameter values can diverge from their actual values) or the ill-conditions in the estimation algorithm. To avoid those situations, a decentralized (i.e., divided into subsystems) system identification approach for an ocean going vessel is presented in this study.

Hence, vessel dynamics are decentralized along their respective actuations of speed and steering control systems in this approach. The main objective of a speed control system is to maintain appropriate vessel speed during its maneuvers, and this is

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associated with thruster–propeller systems [8]. The main objective of a steering control system is to maintain appropriate vessel course during its maneuvers, and this is associated with rudder actuation systems. However, this study is focused on system identification of vessel steering as it is the most important actuation system under course keeping and course changing maneuvers.

There have been a number of linear and nonlinear vessel steering models proposed in the recent literature. Although the linear models in vessel steering are adequate for course keeping maneuvers, they may not be sufficient for course changing maneuvers, where nonlinear vessel steering conditions can also be observed. For instance, a vessel steering model that can preserve nonlinear steering conditions (i.e., stable and unstable steering) is proposed in [9]. These nonlinearities in vessel steering can vary due to the current weather and loading conditions. Therefore, the state and parameter conditions in vessel steering can deviate from the deterministic status. One should note that stochastic ocean behavior can also influence vessel dynamics and that cannot be isolated from the mathematical models of vessel steering. Therefore, a nonlinear vessel steering model associated with stochastic state and parameter variations, to capture realistic ocean navigation behavior, is explicitly considered in this study.

Furthermore, these stochastic state and parameter variations preserve various seakeeping conditions in vessel steering. Stochastic state and parameter variations can generate stable and unstable steering conditions (i.e., nonlinear steering) in an ocean going vessel due to the associated hydrodynamic forces and moments on the hull. One should note that a vessel can encounter stable or unstable steering conditions in a single voyage due to various trim and draft (i.e., loading) conditions [10]. These nonlinear steering conditions can also influence the directional or dynamic stability of a vessel. Furthermore, a vessel associated with poor stable steering conditions can also become unstable due to various water depths [11]. These stable and unstable steering conditions in ocean going vessels can be captured by various maneuvering tests.

The directional stability of a vessel is observed under pull-out maneuvers in sea trials [12]. The stable steering conditions of vessels are observed by spiral maneuvers, and the unstable steering conditions of vessels are observed by reversed spiral maneuvers in sea trials. These sea trials are often conducted under calm water conditions by considering the deterministic state and parameter conditions in vessel steering. However, these deterministic state and parameter conditions in vessel steering cannot hold against environmental disturbances (i.e., varying sea and wind conditions) as mentioned previously. Therefore, a vessel steering system model that can capture nonlinear steering behaviors within the stochastic state and parameter conditions should be considered.

One should note that any realistic model in vessel steering can also degrade under system-model uncertainties. It is suggested that an actual vessel steering system may be of infinite dimensions due to the complex ocean behavior and that cannot be captured by a finite dimensional mathematical model. These system-model uncertainties in vessel steering can be categorized into two groups [13]: parameter uncertainties and unstructured uncertainties. Parameter uncertainties consist of physical parameter variations between the actual vessel steering system and the mathematical model. Unstructured uncertainties consist of the difference between the possibly infinite dimensional actual vessel steering system and the finite-dimensional mathematical model. One should note that parameter uncertainties can also be considered as unstructured uncertainties. Therefore, a mathematical model that can accommodate these unstructured uncertainties in vessel steering should be considered for system identification.

However, a mathematical model with these realistic requirements in vessel steering can accumulate various complexities in system identification. Furthermore, that model can suffer under the process of system identification due to various reasons: the highly nonlinear state and parameter conditions, the underactuation conditions in vessel steering, and the complexities among the inputs (i.e., rudder angle and rudder rate) and the outputs (i.e., vessel heading or course). Feedback linearization is proposed in this study to cope with those challenges, where the mathematical model of vessel steering is simplified while preserving system complexities (i.e., nonlinearities and infinite dimensions). Furthermore, that simplified model in vessel steering is used for the system identification process under an estimation algorithm in this study.

B. *Feedback Linearization*

Feedback linearization can transform a nonlinear system into a fully or partially linear system, resorting to algebraic tools [14]. Therefore, the mathematical model in vessel steering of a complete or specific operating region can be rendered linear, while preserving the system nonlinearities. One should note that this approach is different from conventional linearization, where a system is linearized around an operation point or trajectory; therefore, the system nonlinearities cannot be preserved. Therefore, feedback linearization simplifies the nonlinear mathematical model in vessel steering, thus eventually simplifying the system identification process.

Note that feedback linearization can only be applied to a special class of nonlinear systems that are represented in affine form (i.e., controllable canonical) [15] or, in some situations when there exists a coordinate transformation that can be applied to a system that is not in an affine format [16]. That type of nonlinear system (i.e., affine form) can be transformed by feedback linearization, by inspecting the mathematical model and choosing a feedback control law that removes the model nonlinearities [17]. In general, a complex nonlinear system cannot be linearized by inspection. Therefore, a Lie-derivative-based transformation should be considered to remove the model nonlinearities.

Two types of feedback linearization approaches are presented in the recent literature: full state feedback linearization and partial feedback linearization. Full state feedback linearization maps linearized inputs with the entire state space of the system. However, nonlinear systems often do not satisfy the conditions required to full state feedback linearization, due to the complexities in system outputs. Therefore, these nonlinear systems can only be linearized by partial feedback linearization [18]. One should note that the mathematical model in vessel steering cannot be considered for full state feedback linearization due to underactuation in vessel steering, i.e., a part of vessel steering (i.e., sway motion) cannot be directly controlled and/or observed by rudder actuations. However, when a nonlinear system cannot satisfy full state feedback linearization, an artificial output can be introduced to simulate the required conditions. Therefore, the artificial output will not necessarily achieve the desired output of the system.

Hence, partial feedback linearization is a better approach to simplify a nonlinear system, mapping the linearized inputs to the actual outputs. A part of the mathematical model in vessel steering is considered for partial feedback linearization, where a controllable and/or observable part in vessel steering should be linearized. Therefore, the remaining part of the mathematical model in vessel steering (i.e., uncontrollable and/or unobservable part) is separated from the linearized part and that represents internal dynamics of the system. One should note that system internal dynamics cannot be linearized either by full state feedback linearization or partial feedback linearization.

In general, this uncontrollable and/or unobservable part in vessel steering can raise several issues with respect to the overall system stability. Therefore, the system stability with respect to internal dynamics in vessel steering should be further investigated, however partial feedback linearization is limited to stable internal dynamics. If internal dynamics in vessel steering have locally stable zero under output constrained dynamics [19], then stable internal dynamics can be concluded. This condition has often referred as stable zero dynamics and that can be obtained by observing the system behavior, while the output (i.e., vessel heading) is kept equal to zero in internal dynamics. It is expected that the mathematical model of vessel steering should have stable zero dynamics. Therefore, stable zero dynamics represent stable internal dynamics, where the overall system stability in vessel steering should be stable.

C. State and Parameter Estimation

The partial feedback linearization applied vessel steering model represents a reduced-order version of the nonlinear ship steering system. Therefore, that model has been considered for system identification in this study. However, the reduced-order vessel steering model, which can still accommodate unstructured uncertainties and stochastic parameter behavior, is less complex for system identification, whereas the simplicity in system identification can eventually reduce the design complexities on steering controls. Therefore, the proposed stochastic states and parameters describing the reduced-order vessel steering model are identified, resorting to an extended Kalman filter (EKF). The results are obtained considering a realistic numerical simulator for nonlinear vessel steering, as illustrated in this study.

II. Recent Literature

Various system identification approaches have been applied not only in maritime transportation but also in land [20] and in air transportation problems due to the importance in the design process of navigation controllers [21]–[23]. Thus, system identification of vessel dynamics is discussed in this section. A system identification approach of ship maneuvering based on an extended Kalman filter is proposed by Hwang [24]. However, a larger scale vessel maneuvering model is considered in this approach, with a large number of system states and parameters. One should note that a large number of system states and parameters leads to high computational complexity in the estimation process. To tackle this problem (i.e., a large number of system states and parameters), various maneuvers to estimate selected parts of parameters are introduced. However, each maneuvering condition can introduce considerable variations to the system parameters in vessel dynamics. Therefore, a simultaneous approach to estimate all parameters in vessel dynamics should be considered, thus overcoming those variations and preserving the controller stability and robustness. Moreover, that approach can fail due to the limitations of the estimation algorithms. In those situations, the system should be separated into several parts and the parameters should be estimated on the parts that are required to preserve the system stability and robustness as presented (i.e., under feedback linearization) in this study.

A parameter estimation approach to ship steering dynamics, based on a linear continuous-time model influenced by discrete-time measurements, is proposed by Astrom and Kalstrom [25]. However, the study is limited to a linear vessel steering model. Nonlinear steering (i.e., stable and unstable steering) conditions can be observed by various maneuvers in vessel dynamics as mentioned before. Therefore, a linear steering model can often be degraded under various course changing maneuvers due to nonlinear steering conditions in vessel dynamics.

Ma and Tong [26] proposed an EKF and a second-order filter for parameter identification of ship dynamics. However, the model proposed in this study is limited to a speed control system associated with propulsion controls. One should note that ship steering plays an important role when compared to general ship maneuvers. A parameter estimation approach (i.e., an adaptive procedure applied in back-stepping theory) based on a nonlinear Norrbin model with experimental data of course changing maneuvers is presented by Casado *et al.* [27]. A simplified mathematical model for predicting a short-term path based on the vessel kinematic is presented in [28]. Similarly, a system identification approach of vessel navigation, along a desired path, based on a nonlinear ship maneuvering model, is proposed by Skjetne *et al.* [29], where several experimental results are also presented.

The Nomoto model [30] is one of the most popular approaches to describe the vessel steering conditions. Fundamental properties (i.e., observability and controllability) of the first- and second-order Nomoto models are presented in [31]. The parameter identification of ship steering based on the Nomoto's first-order model can be found in [32], where the calculations of the maneuvering indices are based on zigzag maneuvers. However, these Nomoto-model-based studies are based on deterministic parameter conditions. As discussed previously, parameter stochastic behavior in vessel steering should be assumed under course-changing maneuvers, and this is supported by the experimental data reported in [33], where the estimated hydrodynamic forces and moments are changing under varying maneuvering conditions.

Furthermore, several experimental approaches in system identification of vessel dynamics can also be observed in the recent literature. In general, two types of experiments are conducted in this area: free-steering and captive tests. Free-steering tests are done in ships under sea trails and the behavior of the vessel is observed with respect to rudder angle variations. In captive tests, scaled models of vessels are used and the experimental platforms are forced into scaled environmental conditions [25], [34]. Furthermore, captive tests can be further divided into two sections: static and dynamic tests. Static tests consist of rotating arm tests (RATs), circular motion tests (CMTs), oblique towing tests (OTTs), etc. Dynamic tests mainly consist of planar motion mechanism (PMM) approaches [35].

However, these experimental approaches in system identification of vessel dynamics can degrade due the scale effects when applied to actual vessels [36], where measured hydrodynamic coefficients cannot always be realizable. Nevertheless, large-scale models are proposed in some of these situations to overcome the scale effects. On the other hand, these experimental approaches in system identification are based on vessel horizontal motions, where other motions (i.e., roll and pitch motion) are ignored. Therefore, the nonlinearities associated with other motions (i.e., roll and pitch motion) in vessel dynamics may not adequately be represented in these models. Similarly, deterministic parameter conditions are also assumed in these experiments, and adequate conditions in seakeeping may not be held.

A mathematical model of vessel dynamics based on a recursive neural network is proposed by Moreira and Guedes Soares [37]. Similar approaches, also resorting to neural networks, are proposed and experimentally evaluated by several studies, namely, [38] and [39]. System identification of ship steering based on support vector regression (SVR) [40] and support vector machines (SVMs) [41] can be found in the respective studies. However, the system identification applications based on artificial intelligent approaches (e.g., neural networks) can often degrade under highly nonlinear vessel steering conditions.

An identification process of hydrodynamic coefficients for an ocean going vessel from sea trial data is presented in [33]. Accumulated hydrodynamic forces and moments for surge, sway, and yaw motions are calculated resorting to an EKF and a smoother algorithm. The individual hydrodynamic coefficients are calculated by a regression approach, however, considerable variations between true and estimated hydrodynamic coefficients are reported in that study. System identification of vessel hydrodynamic characteristics based on trial maneuvers of a vessel can also be found in [36]. An EKF-based algorithm with several zigzag ship routes of mild, moderate, and persistent excitation maneuvers are conducted to capture the nonlinear hydrodynamic behavior of vessel parameters in the same study. Due to the large number of states and parameters to be estimated in the vessel dynamic model, some parameters have not been properly identified. As discussed previously, the estimation algorithms (i.e., EKF) can often fail to estimate the required properties under a large number of system states and parameters. However, that can be tackled by selecting a set of states and parameters to estimate in the same system model. Hence, that set should satisfy the controller design requirements, i.e., an appropriate number of states and parameters to preserve the controller stability and robustness.

Therefore, feedback linearization is selected in this study to select a set of states and parameters, i.e., the linearized part of vessel steering, satisfying the above challenges. Then, an EKF algorithm is proposed to estimate the states and parameters that are related to the same part. Moreover, improvements in sensor accuracy and on the increment in the number of sensors available can also further improve the overall EKF performance.

III. Mathematical Model for Vessel Steering

The initial mathematical model in vessel steering is presented (i.e., the second-order Nomoto model [30]) with respect to the heading angle of the vessel $\psi(t)$

$$\psi^{(3)}(t) + \left(\frac{1}{T_1} + \frac{1}{T_2}\right)\ddot{\psi}(t) + \frac{1}{T_1 T_2}\dot{\psi}(t) = \frac{K_R}{T_1 T_2}\left(T_3\dot{\delta}_R(t) + \delta_R(t)\right) \quad (1)$$

where δ_R is the rudder angle, and the respective vessel steering system parameters are T_1, T_2, T_3, and K_R. This model is adequate for course keeping maneuvers, but may be inadequate for course changing maneuvers due to the nonlinear steering conditions. Therefore, the vessel steering model presented in (1) should be modified to accommodate course changing maneuvering conditions. Nonlinear vessel steering conditions, given a rudder angle larger than five degrees, should be represented by a nonlinear function as proposed in [9], where the yaw rate $\dot{\psi}(t)$ is replaced by a nonlinear function $K_R H(\dot{\psi}(t))$. This is called reversed spiral curve and can be approximated as [11]

$$H\left(\dot{\psi}(t)\right) = n_1\dot{\psi}(t) + n_2\dot{\psi}^3(t) \quad (2)$$

where the respective nonlinear vessel steering parameters are modeled using n_1 and n_2. In general, the sign of the parameter n_1 determines the stable and unstable conditions in vessel steering: n_1 is positive in course stable steering and n_1 is negative in course-unstable steering. As the same vessel can experience stable and unstable steering conditions in the same voyage, wide variations on the parameters n_1 and n_2 are expected under course changing maneuvers. Applying (2), the linear vessel steering model in (1) can be modified as

$$\psi^{(3)}(t) = -d_1\ddot{\psi}(t) - d_2\left(n_2\dot{\psi}^3(t) + n_1\dot{\psi}(t)\right) + d_2\left(d_3\dot{\delta}_R(t) + \delta_R(t)\right) \quad (3)$$

where the initial parameters of nonlinear vessel steering are defined as: $d_1 = (1/T_1) + (1/T_2)$, $d_2 = K_R/T_1T_2$, and $d_3 = T_3$. Hence, (3) can be rewritten as [42]

$$\psi^{(3)}(t) = \alpha_1\dot{\psi}^3(t) + \alpha_2\dot{\psi}(t) + \alpha_3\ddot{\psi}(t) + \beta_1\delta_R(t) + \beta_2\dot{\delta}_R(t) \quad (4)$$

where the final parameters of nonlinear vessel steering are defined as: $\alpha_1 = -n_2 d_2$, $\alpha_2 = -n_1 d_2$, $\alpha_3 = -d_1$, $\beta_1 = d_2$, and $\beta_2 = d_2 d_3$. Therefore, the nonlinear mathematical model in (4) is used for system identification of vessel steering in this study. One should note that steering gear dynamic conditions are neglected in this nonlinear vessel steering model because steering gear dynamics are faster when compared with vessel steering dynamics [11]. However, the mathematical model in (4) consists of two control inputs: rudder angle and rudder rate. The simultaneous control of the rudder angle and rate conditions, with respect to the vessel heading, can complicate the controller design process as well as the system identification approaches. Therefore, the nonlinear vessel steering model in (4) is simplified by considering an algebraic transformation.

IV. Nonlinear Vessel Steering Model

As discussed previously, a reduced-order vessel steering model that can preserve nonlinear steering conditions is considered in this section by applying feedback linearization. The feedback linearization step can be summarized as the following tasks [13]: 1) the nonlinear vessel steering model in (4) is transformed into an affine format; then 2) the model validity under full state or partially feedback linearization is investigated by calculating the relative degree of the system (if the system is full state feedback linearizable then input-state linearization will be applied; otherwise, input–output linearization will be applied; 3) the stability of internal dynamics is analyzed as required (i.e., for partial feedback linearization); and finally, 4) an appropriate new control input should be derived.

A. Coordinate Transformation

The nonlinear vessel steering model derived in (4) is considered for feedback linearization. However, one should note that the mathematical this model is not in an affine format. Hence, that should be transformed into affine format by a special algebraic coordinate transformation and that can be written as

$$\begin{aligned} x_1(t) &= \psi(t) \\ x_2(t) &= \dot{\psi}(t) \\ x_3(t) &= \ddot{\psi}(t) - \beta_2 \delta_R(t). \end{aligned} \tag{5}$$

Applying the coordinate transformation in (5), the nonlinear vessel steering model presented in (4) can be written as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= x_3(t) + \beta_2 \delta_R(t) \\ \dot{x}_3(t) &= \alpha_1 x_2^3(t) + \alpha_2 x_2(t) + \alpha_3 x_3(t) + (\beta_1 + \alpha_3 \beta_2) \delta_R(t). \end{aligned} \tag{6}$$

One should note that the rudder rate effects are removed in this model and the rudder angle as the main control input for the vessel steering model is derived. However, this control input (i.e., the rudder angle) appears in two system equations of the modified nonlinear vessel steering model in (6). This can create additional complication on system identification of vessel steering. Therefore, feedback linearization is used to further simplify the modified nonlinear vessel steering model.

B. Full State System Model

The vessel steering model derived in (6) is considered in this section to derive the full state system model, and that can be written as

$$\dot{x}_F(t) = f_F(x_F(t)) + w_F(t) \tag{7}$$

where the respective system states and the system functions can be written as, respectively

$$x_F^T(t) = [x_1(t)\ x_2(t)\ x_3(t)\ \alpha_1(t)\ \alpha_2(t)\ \alpha_3(t)\ \beta_1(t)\ \beta_2(t)\ \delta_R(t)]$$

and

$$f_F(x_F(t)) = \begin{bmatrix} x_2(t) \\ x_3(t) + \beta_2(t)\delta_R(t) \\ \alpha_1(t)x_2^3(t) + \alpha_2(t)x_2(t) + \alpha_3(t)x_3(t) \\ + (\beta_1(t) + \alpha_3(t)\beta_2(t))\,\delta_R(t) \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \tag{8}$$

The full state system noise with zero mean and covariance $Q_F(t)$ values is presented as $w_F(t)$. Hence, the Jacobian of function $E(x_F(t))$ can be written as (9), shown at the bottom of the page.

One should note that stochastic behavior in the parameter of ship steering is assumed hereafter in this study.

V. Reduced-Order Model in Vessel Steering

A. Vessel Steering Model

A reduced-order model in vessel steering is derived in this section. Therefore, the vessel steering model derived in (6) can be rewritten in an affine format [15]

$$\dot{x}_s(t) = F(x_s(t)) + G(x_s(t))\, u_s(t) \tag{10}$$

$$\frac{\partial}{\partial x_F(t)} f_F(x_F(t)) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 3\alpha_1(t)x_2^2(t) + \alpha_2(t) & \alpha_3(t) & x_2^3(t) & x_2(t) & x_3(t) + \beta_2(t)\delta_R(t) & \delta_R(t) & \alpha_3(t)\delta_R(t) & \beta_1(t) + \alpha_3(t)\beta_2(t) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{9}$$

where the respective system states, system functions, and control inputs can be written as

$$\begin{aligned}
x_s(t) &= [\,x_1(t) \quad x_2(t) \quad x_3(t)\,]^T \\
F(x_s(t)) &= \begin{bmatrix} x_2(t) \\ x_3(t) \\ \alpha_1(t)x_2^3(t) + \alpha_2(t)x_2(t) + \alpha_3(t)x_3(t) \end{bmatrix} \\
G(x_s(t)) &= \begin{bmatrix} 0 \\ \beta_2(t) \\ (\beta_1(t) + \alpha_3(t)\beta_2(t)) \end{bmatrix} \\
u_s(t) &= \delta_R(t).
\end{aligned} \tag{11}$$

The vessel heading angle $\psi(t)$ is considered as the output of the vessel steering mode, and can be written as

$$y_s(t) = h(x_s(t)) = \psi(t). \tag{12}$$

Hence, considering the vessel steering model in (10) and the system output in (12), the system validity for full state or partially feedback linearization is considered in the following section.

B. Relative Degree

As the next step of feedback linearization, the validity of full state or partial feedback linearization of the modified nonlinear vessel steering system should be investigated. The applicability in full state or partially feedback linearization can be observed by the relative degree of a system. If the relative degree of a nonlinear system is equal to the order of the system, then the system satisfies full state feedback linearization. If that is less than the system order, then a part of the system (i.e., internal dynamics) cannot be controlled and/or observed by the output. Therefore, partial feedback linearization should be applied to the nonlinear system. The relative degree of a nonlinear system can be calculated by a Lie-derivatives-based transformation. The general concept behind the relative degree with respect to Lie derivatives can be considered as follows: to differentiate the output a number of times until the input appears explicitly. The first Lie derivative of the output in (12) (i.e., vessel steering model) can be written as [43]

$$\begin{aligned}
L_G L_F^0 h(x_s(t)) &= L_G h(x_s(t)) \\
&= \frac{\partial h(x_s(t))}{\partial x_s(t)} G(x_s(t)) \\
&= \begin{bmatrix} \frac{\partial h(x_s(t))}{\partial x_1(t)} & \frac{\partial h(x_s(t))}{\partial x_2(t)} & \frac{\partial h(x_s(t))}{\partial x_3(t)} \end{bmatrix} \\
&\quad \times \begin{bmatrix} 0 \\ \beta_2(t) \\ (\beta_1(t) + \alpha_3(t)\beta_2(t)) \end{bmatrix} \\
&= 0.
\end{aligned} \tag{13}$$

The first Lie derivative resulted in $L_G L_F^0 h(x_S(t)) = 0$. Then, the second Lie derivative of the output in (12) can be written as

$$\begin{aligned}
&L_G L_F^1 h(x_s(t)) \\
&= L_G \left[\frac{\partial h(x_s(t))}{\partial y_s(t)} F(x_s(t)) \right] \\
&= L_G \left[\begin{bmatrix} \frac{\partial h(x_s(t))}{\partial x_1(t)} & \frac{\partial h(x_s(t))}{\partial x_2(t)} & \frac{\partial h(x_s(t))}{\partial x_3(t)} \end{bmatrix} \right. \\
&\qquad \left. \times \begin{bmatrix} x_2(t) \\ x_3(t) \\ \alpha_1(t)x_2^3(t) + \alpha_2(t)x_2(t) + \alpha_3(t)x_3(t) \end{bmatrix} \right] \\
&= L_G [x_2(t)] = [\,0 \quad 1 \quad 0\,] \begin{bmatrix} 0 \\ \beta_2(t) \\ (\beta_1(t) + \alpha_3\beta_2(t)) \end{bmatrix} = \beta_2(t) \neq 0.
\end{aligned} \tag{14}$$

Since the second Lie derivative of the output in (12) is $L_G L_F^1 h(x_s(t)) \neq 0$, therefore, it can be concluded that the relative degree of the system is in the order of 2, where the vessel steering model in (10) is in the order of 3. Hence, the relative degree is less than the system order in the model of vessel steering. Therefore, the vessel steering model in (10) cannot be simplified under full state feedback linearization, but it can be so by partial feedback linearization. This is mainly because a part of the system cannot be controlled or observed by the rudder actuations. It is well known that vessel steering is underactuated, with impacts during its simplification under feedback linearization. Therefore, partial feedback linearization is applied in this study.

C. Partial Feedback Linearization

Partial feedback linearization is applied to (10), linearizing the controllable and/or observable part of vessel steering. Following the procedure described in [43]

$$\begin{aligned}
z_1(t) &= L_F^0 h(x_s(t)) = h(x_s(t)) = x_1(t) \\
z_2(t) &= L_F^1 h(x_s(t)) = \frac{\partial h(x_s(t))}{\partial x_s(t)} F(x_s(t)) \\
&= \begin{bmatrix} \frac{\partial h(x_s(t))}{\partial x_1(t)} & \frac{\partial h(x_s(t))}{\partial x_2(t)} & \frac{\partial h(x_s(t))}{\partial x_3(t)} \end{bmatrix} \\
&\quad \times \begin{bmatrix} x_2(t) \\ x_3(t) \\ \alpha_1(t)x_2^3(t) + \alpha_2(t)x_2(t) + \alpha_3(t)x_3(t) \end{bmatrix} = x_2(t)
\end{aligned} \tag{15}$$

where $z_1(t)$ and $z_2(t)$ are the new states of partial feedback linearization applied vessel steering model. Hence, the reduced-order model of vessel steering can be summarized as

$$\begin{aligned}
\dot{z}_1(t) &= z_2(t) \\
\dot{z}_2(t) &= v_x(t)
\end{aligned} \tag{16}$$

where $v_x(t)$ is the new control input that is often referred to as the synthetic control input. The resulted control input under partial feedback linearization applied vessel steering model can be written as [13]

$$\begin{aligned}
u_s(t) &= \frac{1}{\beta(x_s(t))} (-\alpha(x_s(t)) + v_x(t)) \\
&= \frac{1}{\beta_2(t)} (-x_3(t) + v_x(t)).
\end{aligned} \tag{17}$$

The respective functions in (17) of $\alpha(x_S(t))$ and $\beta(x_S(t))$ can be derived as

$$\begin{aligned}
\alpha\left(x_s(t)\right) &= L_F^2 h\left(x_s(t)\right) \\
&= L_F L_F^1 h\left(x_s(t)\right) \\
&= [0\ 1\ 0]\begin{bmatrix} x_2(t) \\ x_3(t) \\ \alpha_1(t)x_2^3(t)+\alpha_2(t)x_2(t)+\alpha_3(t)x_3(t) \end{bmatrix} \\
&= x_3(t) \\
\beta\left(x_s(t)\right) &= L_G L_F^1 h\left(x_s(t)\right) \\
&= [0 \quad 1 \quad 0]\begin{bmatrix} 0 \\ \beta_2(t) \\ (\beta_1(t)+\alpha_3(t)\beta_2(t)) \end{bmatrix} \\
&= \beta_2(t). \qquad (18)
\end{aligned}$$

D. Internal Dynamics

Hence, the remaining part (i.e., uncontrollable and/or unobservable part) of the vessel steering model in (10) represents system internal dynamics, and can be written as

$$\dot{x}_3(t) + \frac{\beta_1(t)}{\beta_2(t)}x_3(t) - \alpha_1(t)z_2^3(t) - \alpha_2(t)z_2(t) = \left(\alpha_2(t) + \frac{\beta_1(t)}{\beta_2(t)}\right)v_x(t). \qquad (19)$$

Hence, the stability of internal dynamics of vessel steering in (19) should be further analyzed to conclude the overall system stability.

E. Zero Dynamics

The stability of internal dynamics of vessel steering can be observed by its zero dynamics, as mentioned before. Internal dynamics will achieve zero dynamics by assigning the system output (i.e., vessel heading) in (12) to zero, which results in

$$\begin{aligned}
\psi(t) &= x_1(t) = z_1(t) = 0 \\
\dot{x}_1(t) &= \dot{z}_1(t) = z_2(t) = 0 \\
\dot{z}_2(t) &= v_x(t) = 0. \qquad (20)
\end{aligned}$$

Applying the conditions derived in (20) into internal dynamic in (19) of vessel steering, it leads to

$$\dot{x}_3(t) + \frac{\beta_1(t)}{\beta_2(t)}x_3(t) = 0. \qquad (21)$$

The stability conditions in zero dynamics of (21) will determine the overall stability in vessel steering. One should observe that the parameters in vessel steering can always satisfy the conditions of $\beta_1 > 0$ and $\beta_2 > 0$. Hence, it can be concluded that $\beta_1(t)/\beta_2 > 0$. Therefore, considering the Hurwitz conditions, zero dynamics in the remaining part of vessel steering is asymptotically stable (i.e., the poles of zero dynamics are on the left-half plane of the root locus) [44]. Furthermore, it can be observed that the nonlinearities in vessel steering have not been affected by system zero dynamics.

One should note that internal dynamics in (19) that are separated from vessel steering can be a complicated mathematical structure and different from the derived model in (19) with various unstructured uncertainties. Therefore, these unstructured uncertainties in vessel steering can be removed (i.e., separated into internal dynamics) by the proposed approach, where the stability on internal dynamics is only the necessary condition that needs to be satisfied.

F. Reduced-Order State Model

The reduced-order state model of vessel steering in (16) and (17) can be summarized as

$$\begin{aligned}
\dot{\psi}(t) &= r(t) \\
\dot{r}(t) &= x_3(t) + \beta_2(t)\delta_R(t). \qquad (22)
\end{aligned}$$

This linearized part is used for system identification of vessel steering in this study as the reduced-order state model. One should note that the nonlinear part in (19) is separated from the mathematical model of vessel steering in (4). Therefore, all unstructured uncertainties in vessel steering can be accommodated in this part (i.e., the nonlinear part), and can reduce the complexity of system identification. However, the mathematical model presented in (22) is a reduced-order representation of the vessel steering system, and this can still preserve nonlinear steering conditions, as well as unstructured uncertainties. Furthermore, the reduced-order vessel steering model in (22) can also accommodate stochastic behavior in the parameter of ship steering. However, the state $x_3(t)$ is unique in this model and the only parameter relationship is to the nonlinear part of vessel steering. Therefore, it is assumed that the state $x_3(t)$ is another parameter with constant mean and covariance values for system identification of vessel steering.

VI. State and Parameter Estimation

System identification of vessel steering by a state and parameter estimation algorithm is discussed in this section. As proposed previously, stochastic parameters describing the linearized vessel steering model in (22) are considered, resorting to an EKF. This estimation process is divided into three sections: the system model, the measurement model, and the estimation process.

A. System Model

The reduced-order state model of vessel steering derived in (22) is considered in this section, and can be written as

$$\dot{x}_R(t) = f_R\left(x_R(t)\right) + w_R(t). \qquad (23)$$

The reduced-order state system noise with zero mean and covariance $Q_R(t)$ values is presented as $w_R(t)$, and the respective states and the system function can be written as

$$\begin{aligned}
x_R^T(t) &= [\,\psi(t) \quad r(t) \quad x_3(t) \quad \beta_2(t) \quad \delta_R(t)\,] \\
f_R\left(x_R(t)\right) &= \begin{bmatrix} r(t) \\ x_3(t)+\beta_2(t)\delta_R(t) \\ 0 \\ 0 \\ 0 \end{bmatrix}. \qquad (24)
\end{aligned}$$

The respective Jacobian matrix of the function $f_R(x_R(t))$ can be written as

$$\frac{\partial}{\partial x_R(t)} f_R\left(x_R(t)\right) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & \delta_R(t) & \beta_2(t) \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \quad (25)$$

One should note that the full state (7) and the reduced-order state (23) models are presented in continuous time.

B. Measurement Model

The measurement model used for system identification of vessel steering is presented in this section. The observables consist of a selected set of the states in vessel steering, obtained from the various onboard sensors. The measurement model is generally formulated in discrete time because the available sensors provide only measurements at discrete instants. The measurement model in vessel steering can thus be written as

$$z_M(k) = h_M\left(x_R(k)\right) + v_M(k). \quad (26)$$

The respective states and functions can be written as

$$\begin{aligned} z_M^T(k) &= \left[z_\psi(k) \quad z_r(k) \quad z_\delta(k)\right] \\ h_M^T\left(x_R(k)\right) &= \left[\psi(k) \quad r(k) \quad \delta_R(k)\right]. \end{aligned} \quad (27)$$

The measurement noise, with zero mean and covariance $R_M(t)$ values, is presented as $v_M(t)$ and the measurements of heading angle, yaw rate, and rudder angle are denoted by $z_\psi(k)$, $z_r(k)$, and $z_\delta(k)$, respectively. Hence, the Jacobian of function $h_M(x_R(t))$ can be written as

$$\frac{\partial}{\partial x_R(k)} h_M\left(x_R(k)\right) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \quad (28)$$

One should note that the measurement model in (26) is in discrete time.

C. Estimation Algorithm

Finally, the estimation algorithm (i.e., the EKF algorithm) that is implemented to calculate vessel states and parameters in both models (i.e., full state and reduced-order models) is considered in this section [45]. The structure of the EKF algorithm [46] applied to both the full state and reduced-order state vessel steering models in (7) and (23), respectively, with the measurement model in (26) presented in Fig. 1. Therefore, $\hat{x}_R(k^-)$ and $\hat{x}_R(k^+)$ represent the prior and posterior estimated states, respectively, and $K_R(k)$ is the Kalman gain of the reduced-order state vessel steering models.

The EKF algorithm proposed in this study will estimate both the states and the unknown parameters given the capability of capturing vessel steering behavior. One should note that the Kalman and extended Kalman filters have extensively contributed to improvement of various navigation systems in land, air, and ocean transportation [47], [48] under state and parameter estimation applications. In many engineering applications, the nonlinear parameter conditions to be estimated by the EKF

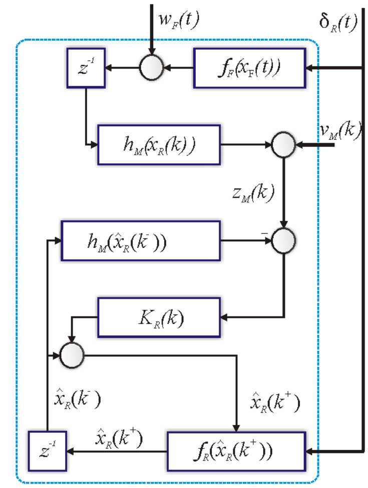

Fig. 1. EKF structure for system identification.

algorithm can lead to successful results [49]. Even though the EKF is a computationally efficient and powerful algorithm, it is a suboptimal recursive filter and can fail to converge in some situations. This challenge has to be overcome in this study by reducing the number of system states and parameters to be estimated using feedback linearization, and with special care in the initialization conditions.

Furthermore, it has been shown that persistent excitation maneuvers (the rudder angle with larger rapid variations) can lead to better estimation of the system states and parameters than the low amplitude constant rudder angle inputs; this is mainly due to the inputs with larger rapid variations exciting the system nonlinearities, which eventually leads to a better parameter estimation process. For vessel steering, this concept is further illustrated resorting to violent maneuvers [36], where the system identification process of vessels can be excited by the larger rudder angle variations within its actuation limitations.

VII. Simulation Results

The simulation results on system identification of vessel steering are presented in this section. Two sets of simulation results for state and parameter estimation are presented in this study, which consists in Figs. 2–6 and Figs. 7–11, respectively. The EKF algorithm that is discussed in this study, is depicted in these simulations, and is implemented on the MATLAB software platform. Persistent excitation on the input rudder angle, between 1.0 (rad) values between starboard and port, is also considered, for better EKF convergence of the vessel parameters. One should note that persistent excitation of the input signal is required for unbiased identification of the system parameters [50].

The parameters from the vessel steering model have been extracted from the study in [51] and the vessel linear parameters are: $T_1 = -16.91$ s, $T_2 = 0.45$ s, $T_3 = 1.43$ s, and $K_T = 5.88$ 1/s. These values are calculated for a tanker with length 350 m at the speed of 5 m/s. The vessel nonlinear parameters are considered as: $n_1 = -1$ s and $n_2 = 1$ s^3/rad^2. One should note that the parameter conditions have been modeled as Gaussian distributions with the respective mean and constant covariance values, to accommodate their stochastic behavior.

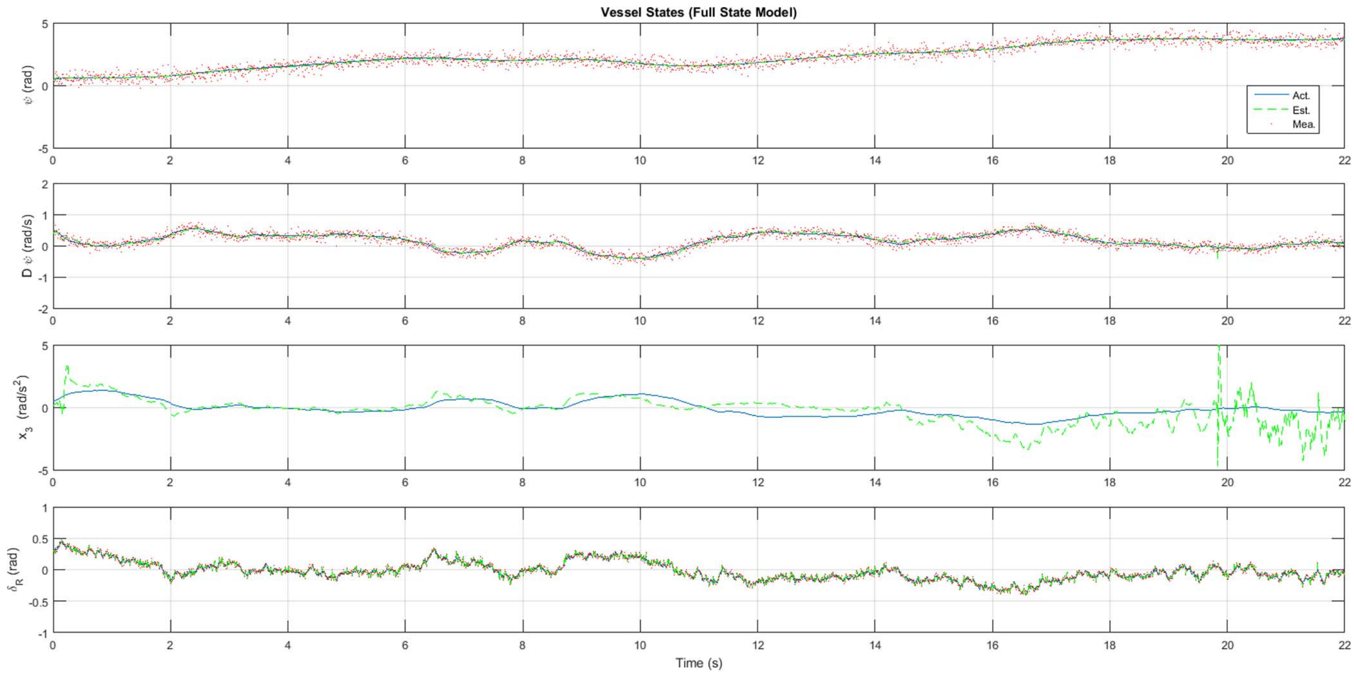

Fig. 2. Vessel states of the full state model (simulation 1).

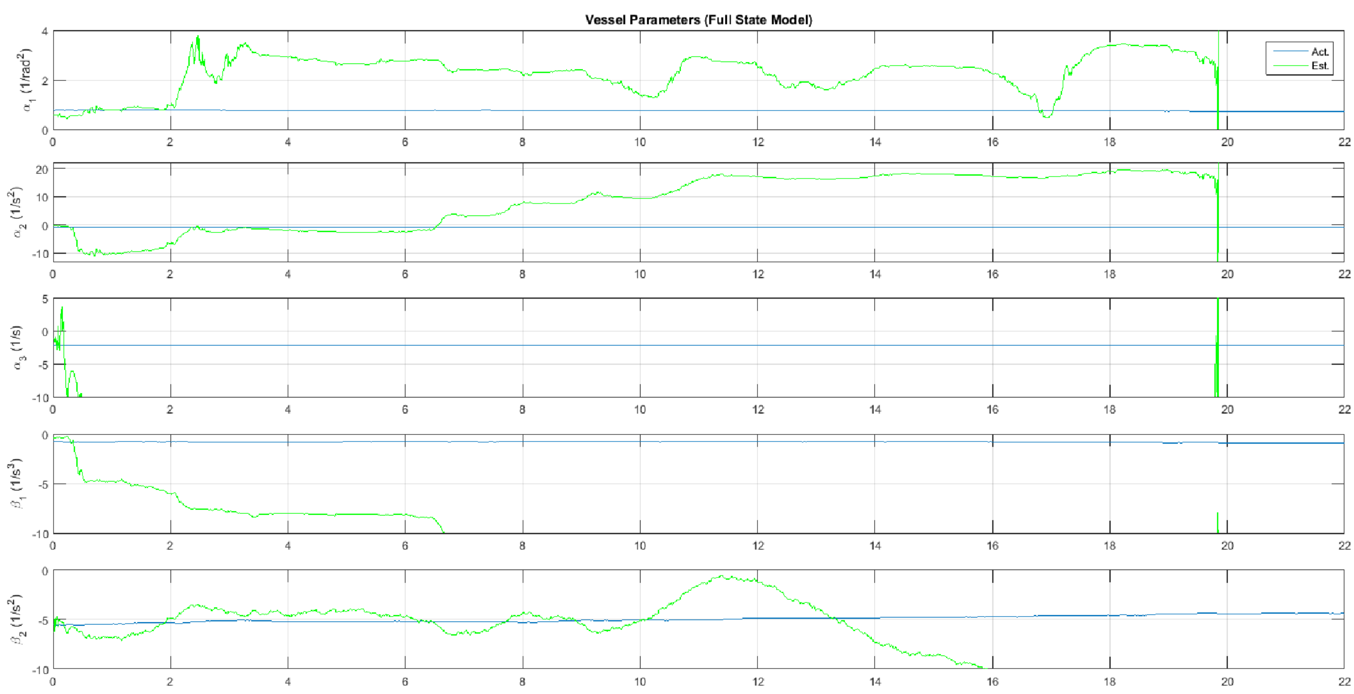

Fig. 3. Vessel parameters of the full state model (simulation 1).

The simulations of the actual (Act.), estimated (Est.), and measured (Mea.) vessel states of the heading angle ψ, the yaw rate $\dot{\psi}$, the state $x_3 = \dot{\psi} - \beta_2\delta_R$, and the rudder angle δ_R, for the full state model in vessel steering (7), are presented in Fig. 2. The EKF has converged the heading angle, the yaw rate, and the rudder angle values quickly due to their measurements. However, the EKF has diverged the state $x_3 = \dot{\psi} - \beta_2\delta_R$, due to the model complexities. Furthermore, the actual (Act.) and estimated (Est.) stochastic vessel parameters of α_1, α_2, α_3, β_1, and β_2 for the full state model in vessel steering (7) are also presented in Fig. 3. The parameters of α_1, α_2, α_3, β_1, and β_2 have diverged in this situation also with the EKF algorithm due to the same model complexities.

Even though the EKF can converge all the parameters in some situations [52], it can often diverge due to the model complexities in vessel steering, as discussed previously. Therefore, a reduction in the system states and parameters in vessel steering should be considered, and this can provide a solution as discussed in the following results. The computational simulations of the actual (Act.), estimated (Est.), and measured (Mea.) vessel states of the heading angle ψ, the yaw rate $\dot{\psi}$, the state x_3, and the rudder angle δ_R, for the reduced-order

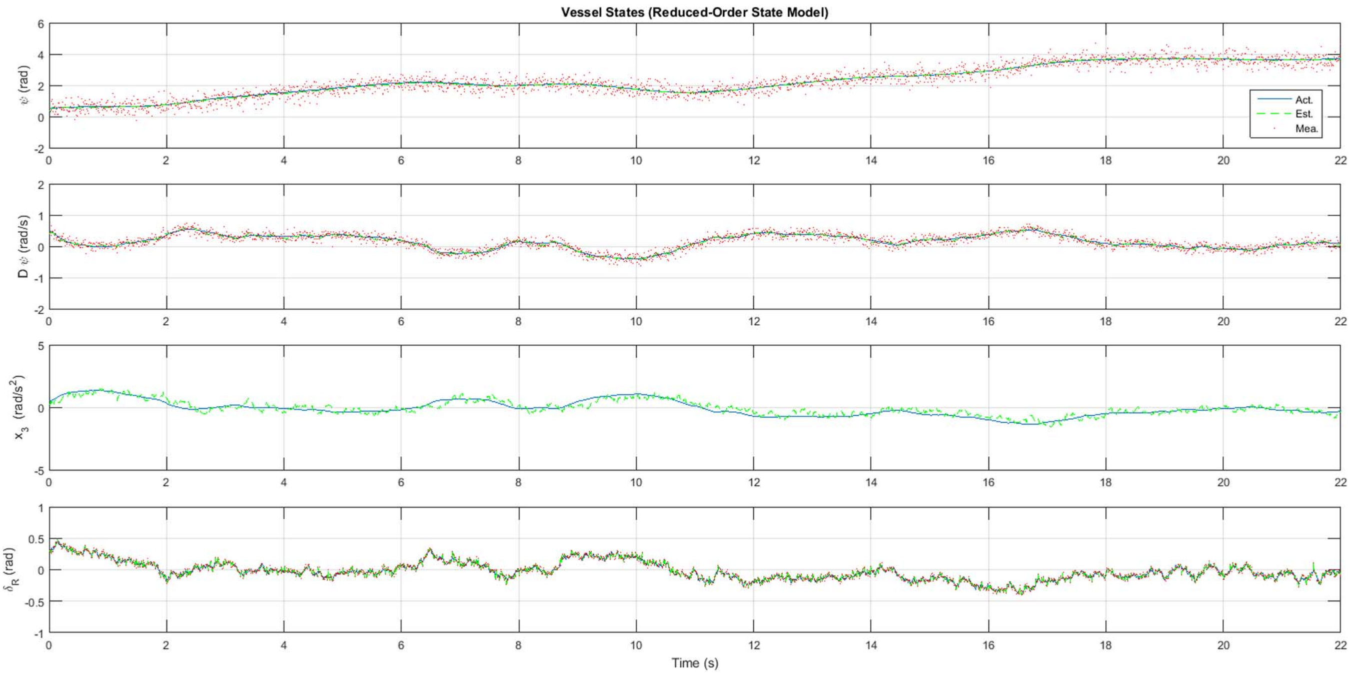

Fig. 4. Vessel states of the reduced-order state model (simulation 1).

Fig. 5. Vessel parameters of the reduced-order state model (simulation 1).

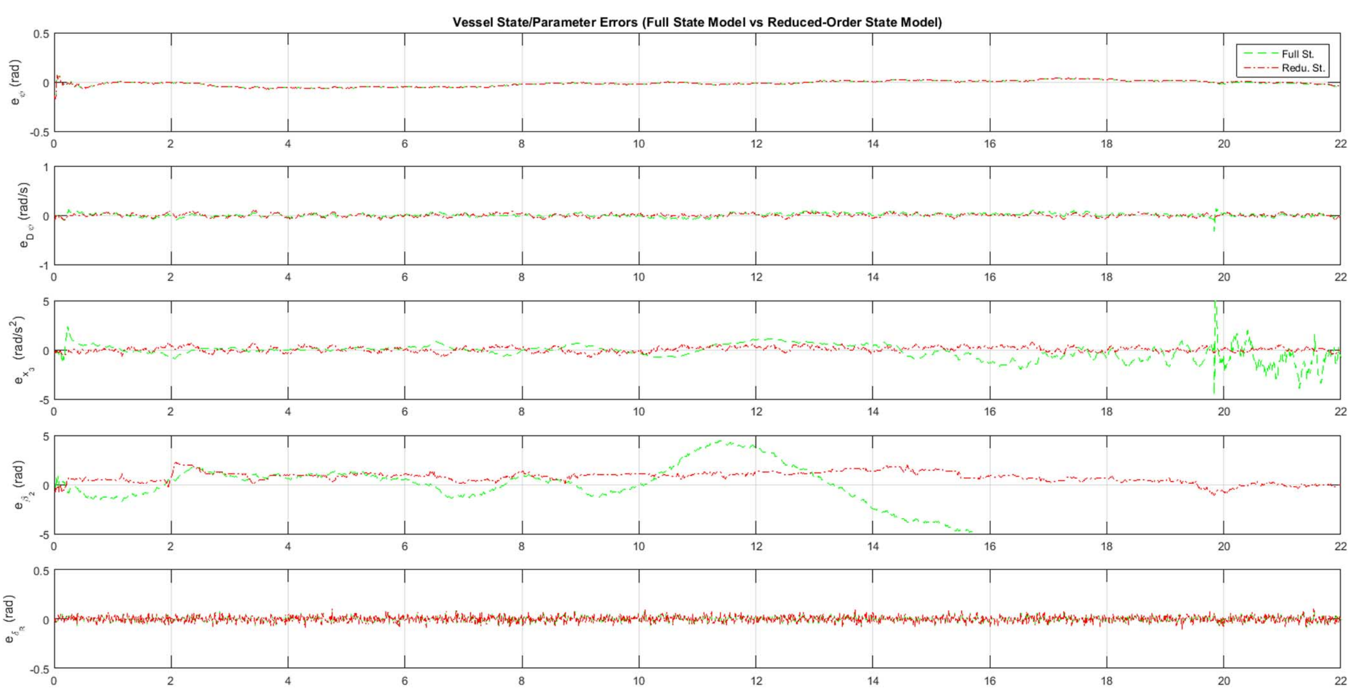

Fig. 6. Vessel states and parameter errors for full state and reduced-order state models (simulation 1).

state model in vessel steering, are presented in Fig. 4. The EKF has converged the heading angle, the yaw rate, the state x_3, and the rudder angle values quickly due to their measurements and the model simplicity in this situation. Furthermore, the actual (Act.) and estimated (Est.) stochastic vessel parameter β_2 for the reduced-order state model in vessel steering is also presented in Fig. 5. The parameter β_2 has converged in this situation with the EKF algorithm due to the model simplicity.

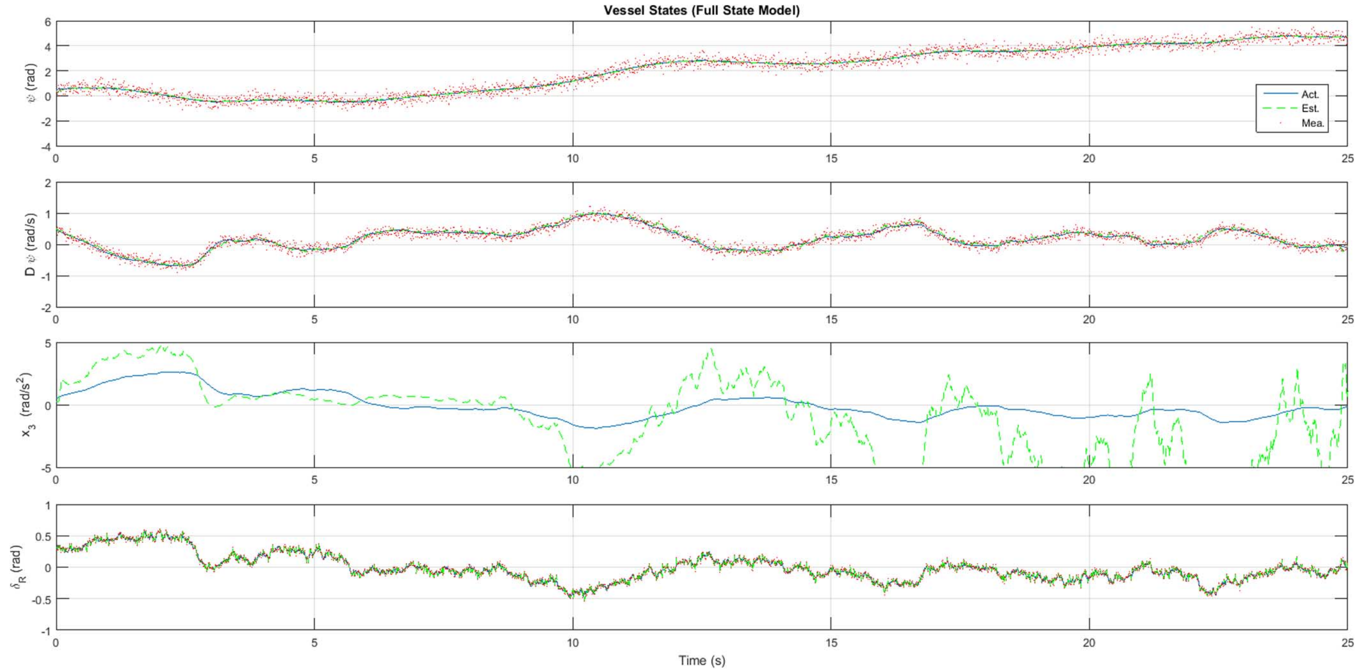

Fig. 7. Vessel states of the full state model (simulation 2).

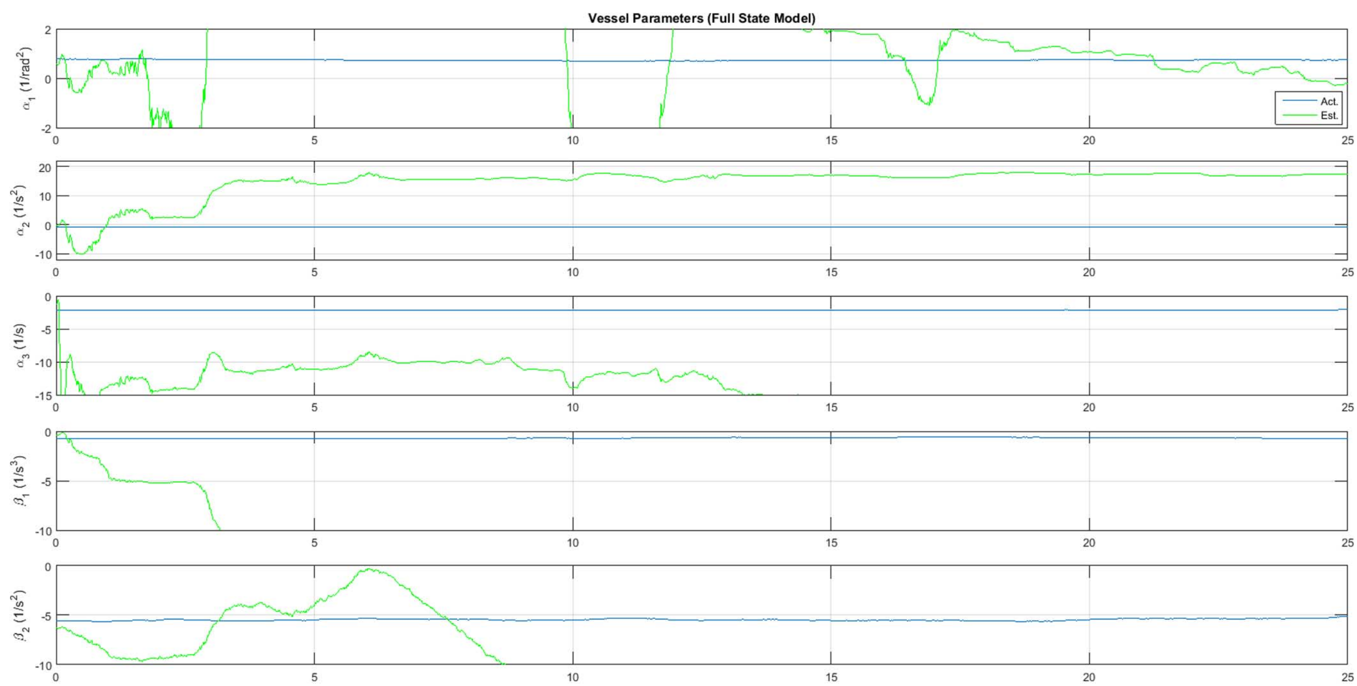

Fig. 8. Vessel parameters of the full state model (simulation 2).

The vessel state errors (i.e., different between actual and estimated values) for the heading angle, the yaw rate, the state x_3, the parameter β_2, and the rudder angle δ_R, for the full state and reduced-order models, are presented in Fig. 6. As presented in the figure, the system state and parameter errors that are related to the full state model have been diverged in many situations, and the system and parameter errors that are related to the reduced-order state model have always been bounded. Therefore, the proposed approach can be used to overcome these challenging situations in system identification. A similar conclusion can be obtained from the second simulation results, which consists of Figs. 7–11.

VIII. Conclusion

System identification of nonlinear vessel steering with unstructured uncertainties is considered in this paper. This consists of applying feedback linearization to reduce the number of vessel states and parameters, where the steering control design process can be simplified. Furthermore, system-model unstructured uncertainties in vessel steering can also be separated

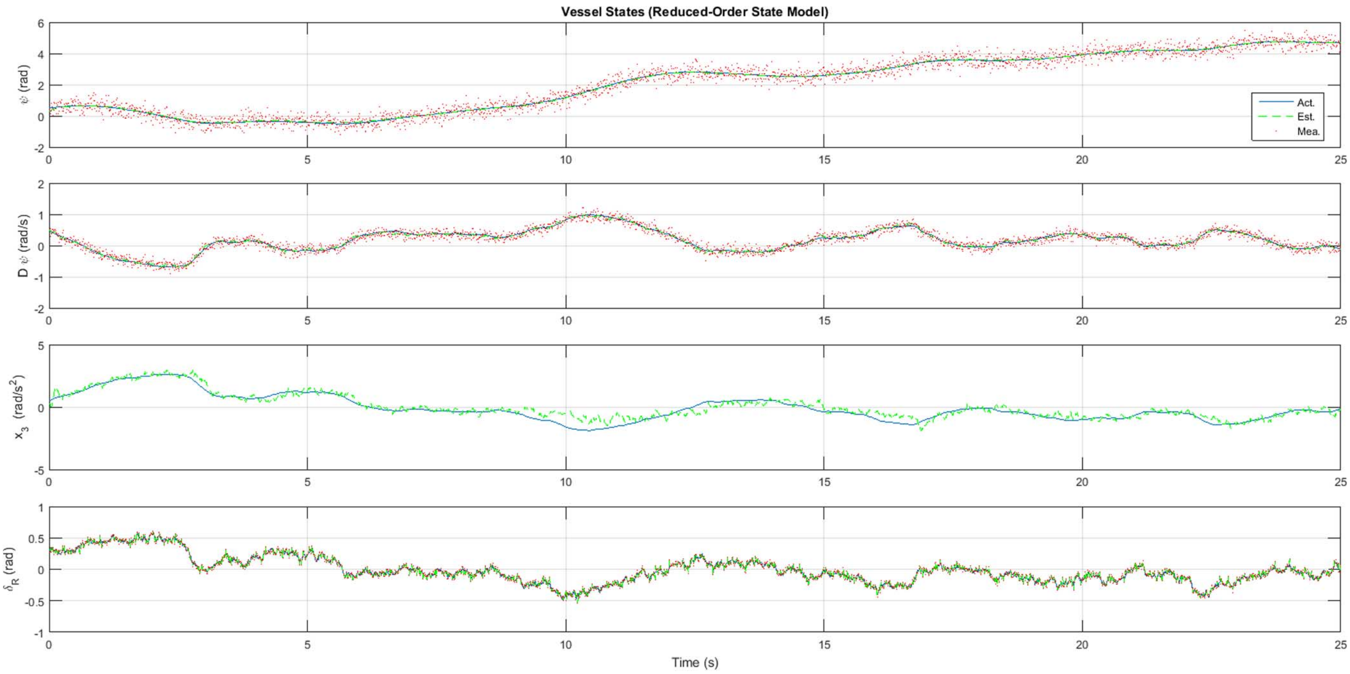

Fig. 9. Vessel states of the reduced-order state model (simulation 2).

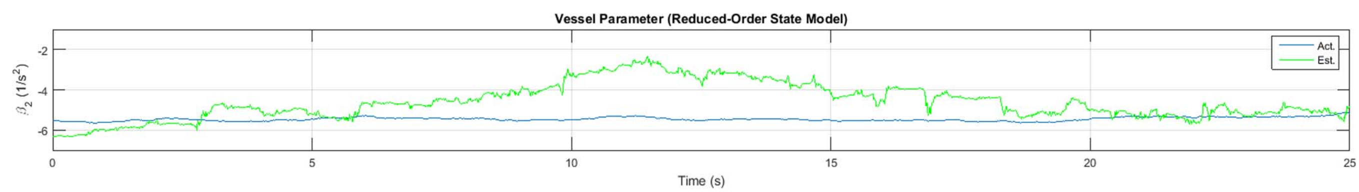

Fig. 10. Vessel parameters of the reduced-order state model (simulation 2).

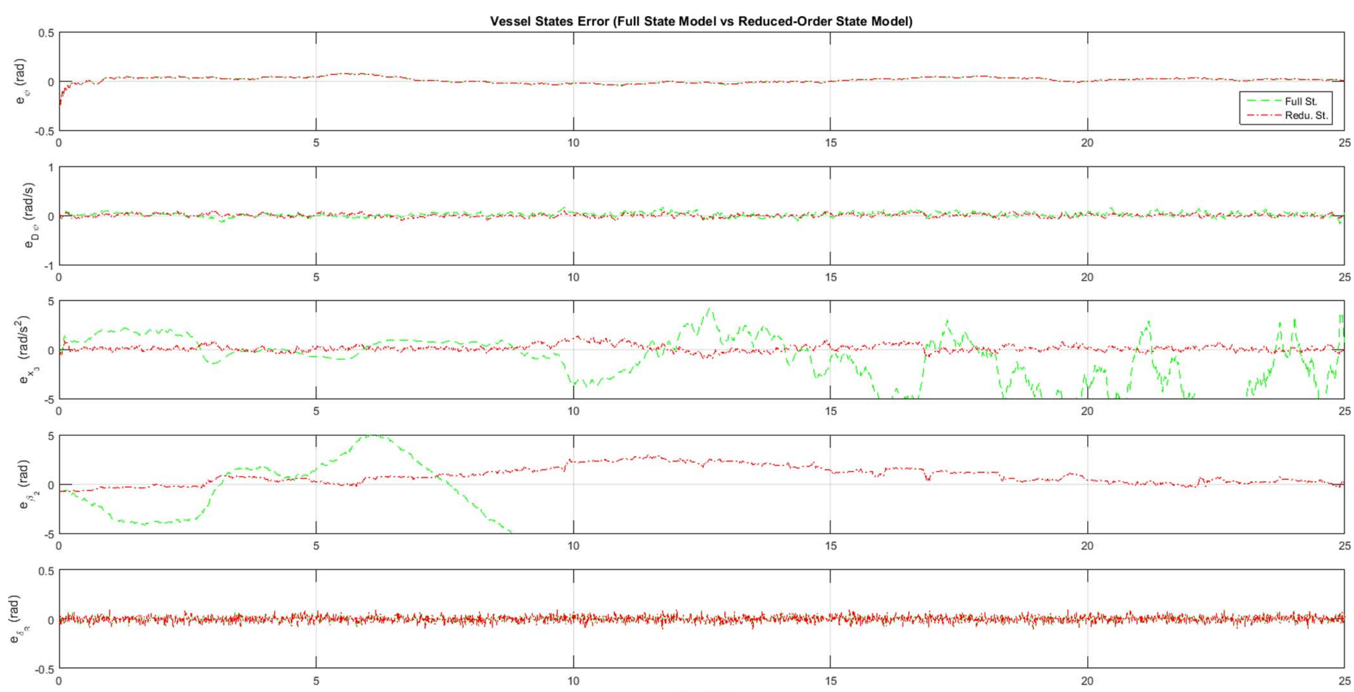

Fig. 11. Vessel states and parameter errors for full state and reduced-order state models (simulation 2).

by considering feedback linearization. Therefore, feedback linearization has linearized a part (i.e., reduced-order model) of vessel steering and has been used for parameter estimation, resorting to the EKF algorithm. The simulation results show that the reduced-order model in vessel steering can successful identify the required states and parameters, with an advantages relative to the full state model in vessel steering, under persistent excitation maneuvers. This has been the main contribution of this approach, and can be used in a wide range of system identification applications.

Even though smooth maneuvers (i.e., zigzag and circular maneuvers) have been extensively used for systems identification of vessel kinematic and dynamic models, this may not excite system identification applications effectively (i.e., it may not excite the nonlinear vessel steering parameters). Furthermore, a large number of vessel states and parameters may also further degrade the system and parameter estimation process. This study concludes that persistent excitation maneuvering conditions with a reduced-order state vessel steering model should be implemented to estimate the required states and parameters of ocean going vessels under varying operational conditions. Therefore, the required states and parameters under a dynamic estimation process can feed into the ship autopilot system, where the stability and robustness in the controller in vessel steering can be preserved.

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